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Classification of Natural Disaster Using Satellite & Drone Images with CNN Using Transfer Learning

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Abstract :- Detection of natural disasters is a very crucial problem to mitigate the damage caused by them. Remote sensing technology can used in detection of certain disasters on an area. We have built a model to detect natural disasters like earthquake, cyclones, wildfires and floods using real time data from satellite and drones. The training data for the model consists of images classified into four classes namely earthquake, cyclones, wildfires and floods. The real-time video stream or a pre-recorded video is passed as the input for detection of calamities. Model takes each casing successively and measures it. For each frame, the probability of all the classes is calculated. Then class label with maximum probability is chosen. The class label is displayed on the top of the frame with a probability calculated by the model. If no disaster is predicted, it shows "normal" otherwise it will display the disaster predicted by the model..

Keyword- ResNet50,CNN,Transfer Learning, Natural Disaster Detection, Image/Video Classification

I. INTRODUCTION

Climate changes every day—some of the time it downpours, other days it's warm climate. Environmental change influences more than temperature. Hotter water changes the patterns of sea flows, influencing the climate designs worldwide. Some places will get more precipitation, which could prompt flooding, while the others will get less, which may cause dry season. Hurricanes could be more grounded, and a proceeding with ascend in ocean level because of dissolving polar ice may push individuals out of their homes.

Aside from catastrophic events, man-made air contamination is additionally common in a large portion of the metropolitan spaces of the world. Towards the beginning of November, brown haze levels crested in Delhi, India. Smoke and exhaust from unregulated yield from activities in northern India e.g. processing plants, vehicles, and even fireworks set out for the Diwali celebration of lights had consolidated to frame a stifling air mixture. Due to ecological and environment changes, today, numerous urban communities are confronting air contamination issue.

The increasing number of catastrophes rouses us to look into these issues and propose an answer dependent on information examination.

Preparing and gauging a lot of information draw out the idea of Deep Learning. Expanded chip preparing capacities, low cost of registering equipment and new advances in AI and data processing are the fundamental purposes behind ubiquity of Deep Learning. Thus, academic and industrial fields look with high interest to deep learning and it has been applied effectively in numerous areas like classification tasks, reduction of dimensions, object identification, NLP etc.

II. LITERATURE SURVEY

Exploration on topographical fiasco identification and acknowledgment on distant detecting pictures has been led in most recent couple of years. Past investigations have essentially focused on identifying changes happened because of catastrophe, contingent just upon sensors [1], and physically change picture preparing procedures , for example, picture variable based math, post-characterization examination and item based change location technique in [2]. For instance, some European nations have made a few accomplishments in avalanche planning, debacle checking and investigating, early admonition, and so forth [3]. To expand the precision of discovery, AI is carried out to work on the proficiency of removing highlight [4]. The greater part of the techniques for avalanche location and acknowledgment incorporate counterfeit visual translation object-arranged strategy [5] and measurable model-based strategies. [6] Suggested various levelled shape highlights in the sacks of-visual words setting to distinguish enormous scope harm.One of the technique used ANN on NOAA-AVHRR satellite images to predict the cyclone movement[7].A lot of writing has been distributed on discovery dependent on AI. Tornado track gauging utilizing counterfeit neural organizations is displayed in [8]. Levee system of New Orleans and dams and dikes of the Netherlands are some of the great efforts to reduce the damaging effects of floods [9]. Perhaps the most renowned practices in profound learning, CNN [10] is making recognition improving outcome in a fiasco. The reach for assessing the event of the catastrophe is restricted because of the lacking number of sensor and accuracy is low. Other than that, the administrators included are unable to cope up with a gigantic measure of satellite symbolisms and distinguish fiasco event in brief timeframe. Subsequently, this might prompt confusion of data or disregard of event of a calamity. In light of this model, it shows the way that it is hard to get to prompt execution enhancement for calamity discovery and the board dependent on past examinations. Therefore, this paper goal is to construct an automated catastrophe detection device via examining the prevalence of a catastrophe in a broader variety through satellite TV for pc and drone photos and tracking each unmarried catastrophe assisted with the aid of using deep studying techniques, i.e. Convolutional Neural Networks primarily based totally ResNet-50 model.

III. METHODOLOGY

Dataset Generation-We begin by scraping images captured by satellite and drone on disaster hit areas. Utilizing the Python programming language, it is feasible to "scratch" information from the web in a fast and productive way. These images are scrapped by searching for a specific term and getting image links through Google images site using Python and JS code. Then, these images are downloaded and stored in a folder. Images consists of cyclone and flood affected areas. Also, images of crop burning and wildfires are included.

Table 1: Details of Dataset

LABEL	NO. OF IMAGES	SIZE
CYCLONE	920	450 MB
FLOOD	1065	433 MB
EARTHQUAKE	1340	562 MB
WILDFIRE	1070	429 MB

ARCHITECTURE

Transfer learning technique is employed to use pre-trained ImageNet weights. Residual Networks (shortly called ResNet) is used as a backbone for many computer vision tasks. Deep Residual Network have convolution, pooling, activation and fully-connected layers stacked vertically up. ResNet uses skip connection to add the output from one layer to another. This reduces the problem of vanishing gradients. The images are prepared to be fed to the network in the pre-processing phase.

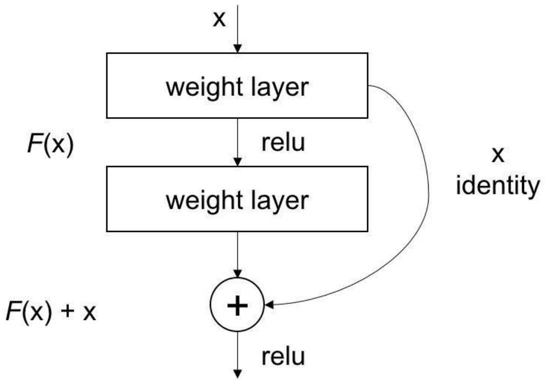

Fig 1: Skip connection in ResNet-50

The architecture consists of four stages. Initial convolution is performed using kernel size of 7 x 7 and max-pooling with 3 x 3 kernel size. The first stage in the network has three blocks with three layers present in each. The kernels in all three layers of the block of first stage are of size 64. In the first stage, block have two layers of kernel size 64 and one of size 128. We use a stride of 2 in the convolution operation in the Residual Block, hence the input size is halved in height and width but the width of the channel becomes two times. On passing to the next stages, the input will be halved and width of the channel doubles. In the model, bottleneck design is employed. Three convolutions 1 x 1, 3 x 3 and 1 x 1 are stacked vertically for every residual function. The 1 x 1 convolution is responsible for restoring the dimensions after reducing them and the 3 x 3 layer remains as a bottleneck with smaller dimensions of input or output. Till the global average pooling layer, all the internal layers are same as in ResNet50. The FC layer is removed and extra pooling of size (7, 7), dense layer, dropout layer (0.5) and softmax after the dense layer are added.

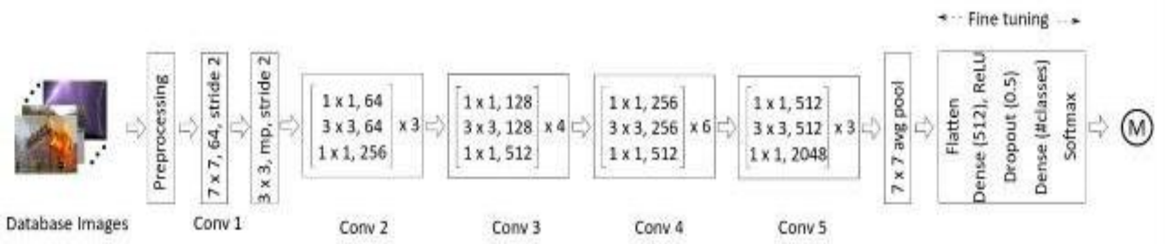

Fig 2: Architecture diagram

Dataset Pre-processing-Information base pictures of fluctuating spatial objectives are resized to the square of dimension 224 followed by change into RGB plan. To keep away from overfitting/under fitting, we follow information increase approach and applied change like turn of 30, zoom of 0.15, width shift and stature shift of 0.2, shear range of 0.15 and even turning some images left-right. This expanded picture is taken as a commitment to the convolutional neural association (CNN) model.

Now it consists of two phases:
Model Training: Instead of preparing CNN model from scratch, we utilized transfer learning method utilizing pre-prepared ImageNet loads. We modified ResNet50 for the model preparation. All the internal layers up to global average pooling (GAP) layer are same as in the ResNet50. We have removed FC layer and average pooling of window size = 7 is added. The pooled map is converted to one dimensional column. The dense layer of 512 neurons is used. The hyper parameter of probability of training a node in the layer is 0.5. Then a dense layer with number of classes as the parameter is added. Softmax activation is used to normalize the output layer values into the probabilities of four classes. The model is prepared with 40 epochs.

Model Testing: The testing of the model is done on the images of calamities from the dataset and on the videos. Firstly, an example test picture dataset from the gathered information base is utilized to assess its presentation. Assessment metrics like recall, accuracy and precision of the framework are produced. Receiver Operating Characteristics (ROC) curve and precision vs recall curve are plotted to test the classification quality. , video recordings are given as input to the model. Each frame is preprocessed like an image as described in the data preprocessing section. The frame is fed to the model and calculation figures the likelihood of the four classes and predicts the class with highest likelihood. Similarly for all the frames coming out of video processing, class of highest probability is predicted. To avoid change of predicted classes frequently, we use running average technique. In this technique, the average of most recent 64 predictions is taken and class of highest probability is found. Difference of probability of this class and combined probability of remaining classes is calculated. If the difference is greater than 0.8, the output frame is labeled with predicted class probability, otherwise labeled ―Normal‖.

IV. Result & Analysis

The classified input dataset was given to the model in 80:20 ratio for training and testing. The results produced are shown below. We observe high accuracy, precision and f1-score for all the four classes. In the macro avg, the column value is taken for each class and then average is taken. For weighted average, proportion of the four classes is considered for average calculation.

	precision	recall	f1-score	support
Cyclone	0.95	0.95	0.95	186
Earthquake	0.99	0.77	0.86	270
Flood	0.74	0.95	0.83	215
Wildfire	0.93	0.91	0.92	215
accuracy			0.89	886
macro avg	0.90	0.90	0.89	886
weighted avg	0.90	0.89	0.89	886

Fig 3: Result of trained model

We plotted the ROC curve to measure the performance of classification of the model. Each point in the curve represents True Positive Vs False Positive at a decision threshold. The graph depicts very good performance of classification as the curve lies close to top left corner of the plot. Area under this ROC curve gives the aggregate performance across all classification thresholds which are possible. The AUC value obtained for the model is 0.98 which is close to 1, indicating high performance of the model for detection of disaster.

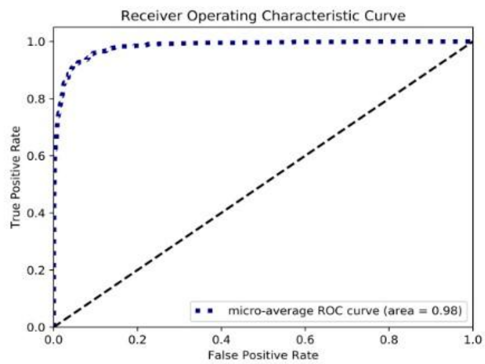

Fig 4: ROC curve

The confusion matrix is plotted for the predicted classes and the actual class label. True label and predicted label are on the vertical and horizontal axis respectively. From analysing the graph we observe that 96% of the cyclone images, 83% of earthquake images, 94% of flood images and 93% of wildfire are predicted correctly. The maximum wrong predictions are observed for flood being predicted for different class images. This can be due to plane surfaces in the flood images in the dataset.

The Precision versus Recall curve is plotted for the disaster detection model. AP has summed up the accuracy review bend as the weighted mean of precisions accomplished at every limit, with the increment in review from the past edge utilized as the weight. The AP precision score over all the classes is obtained to be 0.96 implying that the model can correctly handle the positives without marking too many negative examples as positive.

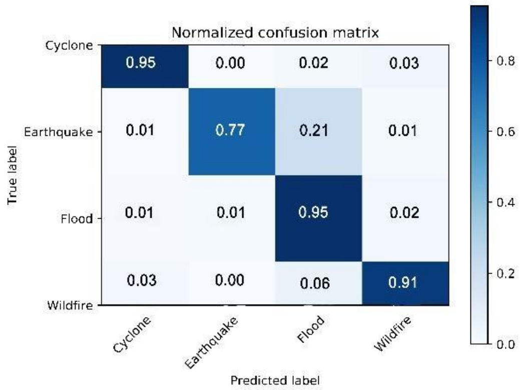

Fig 5: Confusion Matrix

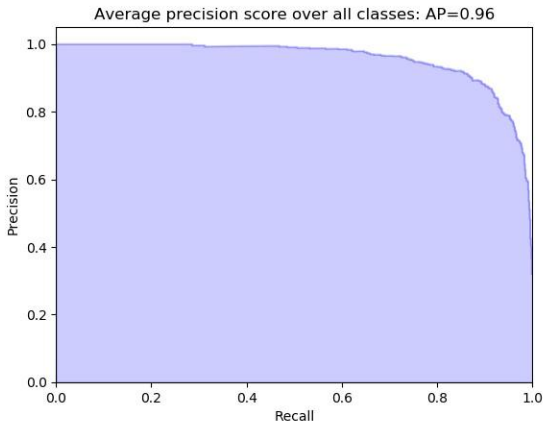

Fig 6: Precision recall curve

The shape of the learning curves depicts high learning rate, decreasing losses and high accuracy of the model. Training loss curve is very steep indicating the high learning rate of the model in the first ten epochs on both training and validation data. Slight overfitting is observed after the eighth epoch as the validation loss becomes more than training loss. The accuracy of the model increases sharply till 4 epochs, then increases slowly afterwards. The difference between the accuracies for the training and validation is very low. There is scope for further learning after 40 epochs but the overfitting will occur as the difference of validation and training losses enlarges.

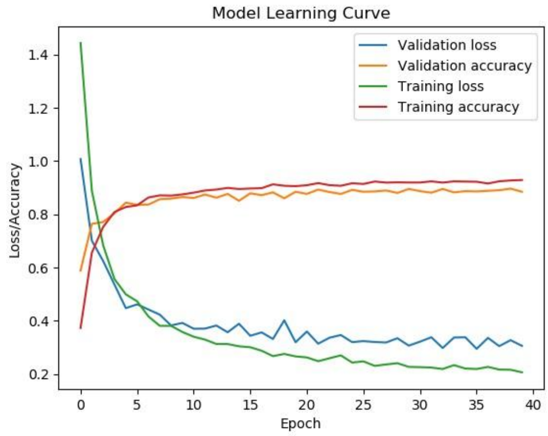

Fig 7: learning curve

Below are the tested images for each of the four classes:-

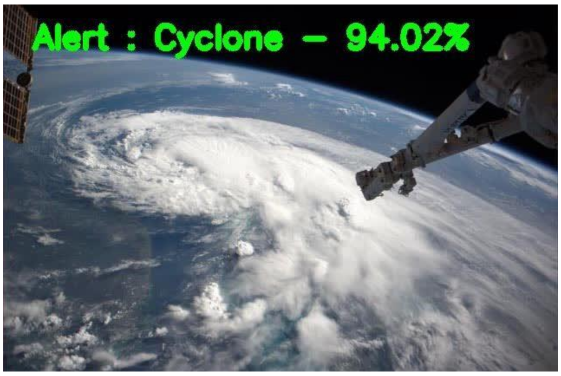

Fig 8: Tested image of Cyclone

Fig 9: Tested image of Earthquake

Fig 10: Tested image of Flood

Fig 11: Tested image of Wildfire

V. CONCLUSION

This model was developed for integrated use of Convolutional Neural Network and pre-trained ResNet-50 model for automated detection of disaster-hit areas using images from satellites and drones. The Model was tested on different satellite and drone images of various geographic locations around the globe.

This method can be used in disaster management centres for detection of the disasters before much harm is caused. It will help operator focus the search for areas affected by the disaster, also, assist in safe path generation to the site of disaster. Early detection of wildfires can help in preventing rise of air pollutants.

Based on experiments conducted, we see many areas to extend and improve this research. Highquality satellite images and investment in highly robust unmanned aerial vehicles will be a further enhancement.

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